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Ecological Efficiency Based Ranking of Cities: A Combined DEA Cross-Efficiency and Shannon's Entropy Method

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Abstract: In this paper, a method is proposed to calculate a comprehensive index that calculates the ecological efficiency of a city by combining together the measurements provided by some Data Envelopment Analysis (DEA) cross-efficiency models using the Shannon's entropy index. The DEA models include non-discretionary uncontrollable inputs, desirable and undesirable outputs. The method is implemented to compute the ecological efficiency of a sample of 116 Italian provincial capital cities in 2011 as a case study. Results emerging from the case study show that the proposed index has a good discrimination power and performs better than the ranking provided by the Sole24Ore, which is generally used in Italy to conduct benchmarking studies. While the sustainability index proposed by the Sole24Ore utilizes a set of subjective weights to aggregate individual indicators, the adoption of the DEA based method limits the subjectivity to the selection of the models. The ecological efficiency measurements generated by the implementation of the method for the Italian cities indicate that they perform very differently, and generally largest cities in terms of population size achieve a higher efficiency score.

Keywords: cross-efficiency; data envelopment analysis; Shannon's entropy; ecological efficiency; cities; ranking; Italy

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1. Background

In the last decade, cities have gained a greater centrality in the economic and social growth of nations. The recent report delivered by the Brookings Institution indicates that in 2014 the economies of the 300 largest metropolitan areas accounted for 47% of global gross domestic product (GDP) and 38% of GDP growth [1]. According to recent estimates provided by Seto *et al.* [2], more than 80% of the national gross domestic product (GDP) is generated in urban areas. A recent worldwide research conducted by the McKinsey Global Institute on a sample of 600 cities estimates that between 2010 and 2050, the GDP of these cities is expected to double, while 23 megacities—cities having more than 10 million inhabitants—in 2007 generated 14% of global GDP [3].

People move to and live in cities to have access to better jobs, education, health care, goods and services. More than half of the human population over the world is living in cities and towns, and, in the next decades, the number of people expected to live in cities will grow to 75%, while population growth over the next 25 years will be concentrated in cities and towns [4,5]. The most urbanized areas are located in the American and Europe continents, respectively having about 80% and 70% of all inhabitants residing in cities and towns. However, while cities are the primary source of economic development and social prosperity, and house more than half of the world population, they are large users of resources, responsible for about 2/3 of energy demand and greenhouse gas emissions [5]. The recent rapid and intense urbanization has often resulted in an over consumption of water, energy, raw materials, land, and production of waste and air pollution. Poor environmental quality and ecological efficiency, together with a scarce infrastructure development and traffic congestion, negatively affect the economic competitiveness, livability, and attractiveness of cities [6,7].

An important issue related to the implementation of an effective urban development strategy aimed at improving the ecological efficiency of a city is the adoption of a measurement framework, a set of performance indicators and, eventually, a synthetic index to rank and benchmark cities. The measurements provided by such indicators and the comprehensive index may be a useful tool to evaluate the success of the policies adopted by local governments to make cities more ecologically efficient, and, if necessary, to revise urban development plans and projects.

Objectives

Measuring and comparing the ecological efficiency of cities have become important elements to assess their livability and the performance of policies adopted by local governments to improve city environmental sustainability and attractiveness [8]. Cities that are more ecologically-efficient are able to reduce the over consumption of resources by minimizing the use of energy, materials, water and land, enhancing recyclability and lower the impact on environment by minimizing air pollution, not treated black and grey water discharges, waste disposal, as well as supporting the adoption of facilities for the production of energy from renewable sources [9].

Several measurement guidelines, frameworks, set of indicators and indices have been proposed by public organizations, consulting bodies and academic scholars. However, these have a number of shortcomings that make them not very useful for ranking cities. Particularly, many shortcomings are due to the model implemented to measure the ecological efficiency indicators and the way different indicators are aggregated to generate a unique measurement. Composite indices are increasingly used for performance monitoring, conducting benchmarking studies, and communicating the outcome of public policies. The main advantage associated with the utilization of a composite aggregate index is related to its intrinsic capability to provide a comprehensive and effective view of a certain phenomenon and to generate a ranking and compare different units under evaluation [10]. Generally, equal weightings are used to aggregate the different dimensions or indicators to generate an aggregate index. However, when multiple weightings are adopted, there are no sound justifications for the choice of different weights. Furthermore, often aggregate indexes available in literature do not provide an acceptable discrimination between units.

This paper proposes a comprehensive index based on the calculation of Data Envelopment Analysis (DEA) cross-efficiencies and Shannon's entropy index to rank cities with respect to their ecological efficiency score. This index has a number of advantages when it is compared to indexes proposed in the academic and industry literature. Particularly, it uses an endogenous weighting scheme to aggregate partial indicators that is generated from data themselves, avoiding the adoption of any subjective expert judgment. In addition, this index can be easily customized to the specific characteristics and needs of the context and to the availability of data to generate a more effective measurement of the city ecological efficiency by including different sets of indicators. Finally, it has a good discrimination capability. The index is used to compare and rank 116 provincial capital cities in Italy. While sustainability is a complex and multifaceted concept, this paper privileges the ecological dimension of it and a strict conceptualization of ecological efficiency circumscribed to environmental issues is adopted. As there is no agreement among scholars about the model that should be implemented to evaluate resource and environment efficiency, the methodological setting adopted to calculate the ecological efficiency of cities uses several DEA models to simultaneously measure environment and resource efficiency. Moreover, because each model calculates the city ecological efficiency as a cross-efficiency score from different perspectives, results from different DEA models are combined together by means of the Shannon's entropy index.

The rest of the paper is organized as follows. Section 2 reports an in-depth literature survey that focuses on the measurement of ecological efficiency both from a practice and an academic orientation;

Section 3 illustrates the method to compute the ecological efficiency of cities, while Section 4 shows and discusses some major results emerging from the application of the method to a case study relative to a sample of Italian cities. Finally, Section 5 presents some concluding remarks.

2. Measuring Ecological Efficiency: A Literature Survey

Quantifying sustainability development has been a major concern of policy makers and academic scholars, and ecological efficiency indicators have been widely adopted to measure the sustainability of cities. The following sections illustrate some major contributions on the measurement of ecological efficiency both from practice-oriented and academy-oriented perspectives.

2.1. The Practice-Oriented Contribution

A variety of recommendations and guidelines have been proposed relative to the design, meaning and quantification of ecological efficiency indicators [11]. Several international organizations and NGOs have proposed measurement frameworks and indicators to assess environmental sustainability of urban areas or regions, by adopting some theoretical multidimensional models aimed at conducting benchmarking studies at a local level [12], at the country level [13], at the international level [14,15], and in the developing countries of the world [16]. The adoption of a set of standardized sustainability indicators is important to perform effective benchmarking. Indeed, as Olsthoorn *et al.* [17] claim, environmental indicators are usually constructed and applied by organizations on the basis of their specific standpoints. Furthermore, these indicators are often arbitrary and reflect only some dimensions of environmental sustainability and performance.

In 2011 the United Nations Economic and Social Commission for Asia and the Pacific (UN-ESCAP), the United Nations Economic Commission for Latin America and the Caribbean (UN-ECLAC), and the United Nations Human Settlements Program (UN-Habitat), in partnership with the Urban Design Lab of the Earth Institute of the Columbia University have jointly released the “Guidelines for developing eco-efficient and socially inclusive infrastructure”, which provide practical tools for city planners and decision makers to reform urban planning and infrastructure design in developing countries, particularly in Asia and Latin America, according to the principles of ecological efficiency and social inclusion [18].

The Global Reporting Initiative has carried on a research project supported by the World Resource Institute, the United Nations Environment Programme (UNEP), several environment and social associations, the World Business Council for Sustainable Development (WBCSD) and certification agencies to define the “Sustainability Reporting Guidelines” as a common standard [19]. The Yale University has developed the global Environmental Performance Index (EPI) that is adopted to conduct benchmarking studies at both the national and provincial levels [20,21]. In the UK, the Sustainable Development Unit of Government and the Central Local Information Partnership Task Force on Sustainable Development (CLIP), together with a number of local governments have designed a set of indicators covering three dimensions of sustainability: environment, society and economy.

Since 1992, after the adoption of the Maastricht Treaty, the European Commission has showed concerns towards environmental sustainability. After the European Council held in Gothenburg in July 2001, sustainability development has become a major goal of the EU policies and a concern of EU countries. Since then, sustainable development indicators have become useful tools to measure and evaluate progress towards sustainable development in Europe. In 2008 the European Commission adopted a specific strategy for Climate Action. According to this strategy, the Member States will reduce their greenhouse gas emissions by at least 20% and boost the generation of energy from renewable sources to 20% of total consumption by 2020. Furthermore, the European Commission set the goal to reduce its primary energy consumption by 20% by 2020. This strategy stressed the need for EU countries to increase energy efficiency. In 2013, the European Commission published the results of a survey conducted in 2012 that focused on the perception of the quality of life in 79 European cities and major suburban areas. The survey evaluated quality of life as a variable dependent on the perceived quality of relevant public services (health, transport, education, cultural and recreational activities, road cleaning, parks and public land, road maintenance); the perceived quality about some issues related to collective life in the cities (e.g., sport facilities, shops, job offer, housing, environment pollution); and the perceived quality about some personal issues of participants to the survey (e.g., overall satisfaction about life, job, *etc.*). This survey was fundamentally qualitative in nature. The statistical office of the European Union—EUROSTAT—since 2004 provides statistics on some themes relevant to Europe, and, particularly, on transport, environment and energy, sustainable development, and quality of life. Data and indicators are freely available for research purposes [22].

There are a number of empirical studies aimed at identifying and measuring sustainability indicators and, finally, developing aggregated indices that are performed by private organizations.

The Economist Intelligence Unit (EIU), the research and analysis division of The Economist Group, sponsored by Siemens, conducts a yearly research project that covers more than 120 cities worldwide to calculate the Green City Index in order to provide city stakeholders with insights on better environmental policies and best practices [23]. Since 2009, the Green City Index (GCI) evaluates cities' sustainability on about 30 indicators. In particular, the GCI uses data relative to CO_2 emissions, energy consumption, buildings characteristics, utilization of land, transport infrastructure, water and sanitization, waste collection and treatment, and air quality. The method that calculates the CGI uses both qualitative assessments of the city environmental policies and quantitative measurements available in official public databases. The calculation of the index is very flexible as it takes into account data availability. Therefore, the structure of the index changes from country to country.

The Dual Citizen LLC—a USA based consulting company—publishes the Global Green Economy Index™ (GGEI) that provides a measurement of the sustainability performance of 60 countries and 70 cities. Since 2010, this performance index is constructed by aggregating 32 indicators, classified over four main dimensions (leadership and climate change, efficiency sectors, market and investment, environment and natural capital) [24].

The global consulting company Mercer HR has developed a methodology to rank cities with respect to the level of quality of life. The ranking index utilizes 39 indicators grouped in the following categories: political and social context, economical context, cultural context, health, education, public services and transport, leisure, consumption goods, public housing, environment [25]. The weekly newspaper "The Economist" employs data collected by the Mercer HR survey to develop a different index to rank cities in a smaller sample.

Every year, the European consultancy firm Arcadis calculates the Sustainable Cities Index for a sample including the more important 50 cities in the world. Cities are classified according to three sub-indices—People, Planet and Profit. These indices are constructed using indicators that measure environmental quality, such as energy consumption, greenhouse gas emissions, amount of energy generated from renewable sources, and waste recycling rate. [26,27].

The international technical literature also includes the following indices, which for the sake of brevity are only listed here: Climate Change Performance Index [28], Environmental Performance Index [29], Global Cleantech Innovation Index [30], Green Economy Report [31], Low Carbon Economy Index [32], Renewable Energy Country Attractiveness Index [33].

In Italy, in 2010, the National Council for Economics and Labour (CNEL) and the National Statistical Institute of Italy (ISTAT) jointly launched the BES project—*Benessere Equo e Solidale*—aimed at evaluating citizen wellbeing in Italian major cities [34]. The project utilizes a hierarchical frame of indicators grouped in 12 relevant higher-level indices. The second order indicators include measurements relative to the integrated water service, air quality, parks and urban green, road cleaning, urban waste collection and treatment. However, the BES project does not provide a synthetic final index to rank cities. Some indicators are available only at the regional level, while some indicators are available at the city level too.

Since 25 and 20 years, respectively, the two most important Italian economic newspapers—the Sole24Ore and ItaliaOggi—every year carry on separate surveys that deliver two rankings of the Italian provincial capital cities with respect to the quality of life. Particularly, the Sole24Ore study utilizes a set of 36 indicators articulated into six thematic areas (standard of living, business and jobs, environment and public services, crimes, population, leisure). While the thematic areas remain unchanged, the individual indicators of each area can be modified or substituted by new indicators to provide a more articulated evaluation of the city quality of life [35]. However, changing the set of indicators and the weighting scheme from year to year can make the rankings and comparison of cities meaningless. The survey performed by ItaliaOggi evaluates the quality of life in the Italian provinces adopting a set of 77 indicators clustered into eight main areas, which are weighted differently. The project compares only provincial areas and provides more in depth information for a limited number of large cities [36].

The project *Ecosistema Urbano* promoted by Legambiente, a nonprofit green association, has a greater focus on environmental issues and the multidimensional sustainability indicators are used as a reference to develop the "environment" thematic area of both surveys carried on by Sole24Ore and ItaliaOggi [37]. The project Ecosistema Urbano has now developed a well-accepted set of 20 environment indicators that assess quality, pressure and management of environmental resources and are measured year by year for all Italian provincial capital cities. These indicators are aggregated to generate a single index and obtain a unique ranking. Every year, cities showing better environmental performance are awarded a prize.

Finally, several local governments in Italy carry on customer satisfaction survey based on the usage of a set of indicators that often have been purposefully designed. However, many times the set of indicators is not based on the use of variables and measurements that have been previously scientifically validated. Indeed, as local governments try to promote cities as livable, green and environmentally sustainable, indicators are chosen *ad hoc* to evaluate only some aspects and measure the achievement of improvement goals that are easily achievable.

2.2. The Academy-Oriented Contribution

Several scholars have suggested methodological frameworks and indicators to measure the ecological efficiency of urban and regional areas. Mori and Christodoulou [38] reviewed major sustainability indices—Ecological Footprint (EF), Environmental Sustainability Index (ESI), Dashboard of Sustainability (DS), Welfare Index, Genuine Progress Indicator (GPI), Index of Sustainable Economic Welfare, City Development Index, emergy/exergy, Human Development Index (HDI), Environmental Vulnerability Index (EVI), Environmental Policy Index (EPI), Living Planet Index (LPI), Environmentally-adjusted Domestic Product (EDP), Genuine Saving (GS)—and finally discussed conceptual requirements necessary for building an index useful to measure city sustainability. In particular, they claim that the availability or the *ad hoc* creation of a set of indices and/or indicators is an important part of the evaluation of city sustainability.

Literature also suggests sets of indicators and aggregated indices that encompass specific dimensions of urban sustainability, such as energy use [39,40], and water consumption [41]. However, even though the importance of indicators and indices is well acknowledged, there is no agreement about the choice of the indicators and the construction of aggregate indices. Nan and Williams [42] conducted an in-depth historical review on the literature relative to the eco-city and related-concepts, and the performance indicators commonly used for evaluating the sustainability of urban areas. The scholars found that there are several definitions of eco-cities that privilege different dimensions of sustainability and eco-efficiency and even though there has been an effort to integrate these concepts there is no consensus about what dimensions are more or less important. The authors assert ([42], p. ii) "[...] *there is some high-level consensus on the types of phenomena that should be measured in evaluating sustainable, green, eco-, and similarly labeled cities. All indicator systems measure performance related to energy and climate change. Fewer, but still a majority, measure air quality and land use impacts. Even fewer, but still a majority, measure water quality and social health impacts. Waste, transportation, and economic impacts are least commonly measured, but nevertheless are measured by a majority of indicator systems. Despite some consensus on the most important general categories to be measured, there is little consensus about the priority issues to be* *evaluated in each category. There is also little agreement on the methodology by which indicators for each of these areas should be chosen other than relying on data that are already available and on expert opinion regarding what indicators can best be used to measure progress. Threshold benchmarks are not commonly used, and there is little agreement on how indicators or indicator categories should be weighed against each other in forming an aggregated score that could be assigned to a city if a single summary indicator is desired*."

In general, scholars implement different methods and approaches to generate measurements to evaluate sustainability and ecological efficiency of cities, *i.e.*, ecological footprint analysis (EFA) [43,44], emergy accounting [45], urban metabolism analysis [46], ratio-approach [47], parametric and non-parametric methods (e.g., stochastic frontier analysis and DEA) [48–50], and Analytical Hierarchy Process (AHP) [51].

Implementing these methods and approaches has both advantages and disadvantages. Li *et al.* [52] proposed a method based on the calculation of the ecological footprint as an aggregate environmental indicator for evaluating the eco-efficiency of residential development at city level. The method was implemented to compare three Chinese cities. However, the scholars regret that data collection and analysis was very complex and time consuming. Geng *et al.* [53] used ecological footprint analysis for evaluating urban sustainability and comparing two industrial cities in China and Japan. As they claim, even though the ecological footprint analysis is a useful method for evaluating city sustainability, it has some shortcomings. The difficulty to get accurate information about products' life cycles in the case of long and complex production chains, problems related to double-counting, and a lack of an in depth knowledge about the production processes make the implementation of the method not easy and not effective.

A number of researchers use the "emergy" approach to obtain a comprehensive way to value an ecological system that produces goods and delivers services in terms of the amount of energy, which is used directly and indirectly and is conveniently expressed in solar emjoules as a measuring unit [54]. For instance, Pizzigallo *et al.* [55] used an emergy based analysis to evaluate the environmental sustainability of the Province of Modena in Italy. However, this approach has raised some criticism for its being idiosyncratic, computationally complex and data intensive [56]. Scholars have also adopted the metaphors of the living organism and the metabolic process to describe the urban ecosystem and the economic and social activities that people, businesses and infrastructure assets perform when resources are consumed and goods and/or services are produced [57,58]. The Urban Metabolism Analysis has been utilized as an accounting tool to measure the balance between the material flows in cities and, finally, develop eco-efficiency indices [46]. The implementation of this latter approach that is based on the analysis of material flows employs more practical measuring units that the non-academic stakeholders can more easily understand. However, the approach has been criticized [59]. Indeed, the suitability of the Urban Metabolism (UM) framework in applying the concept of the city as a biophysical system has been questioned, emphasizing "[...] *a weakness of UM as the tendency to conflate organism and ecosystem, often using the terms interchangeably*" ([59], p. 757).

Yin *et al.* [60] used measurements of ecological efficiency indicators for evaluating the progress towards sustainability of provincial capital cities in China. Wang *et al.* [61] conducted case study analysis to evaluate the progress of ecological construction in the Shandong province in China by means of a pre-set of qualitative and quantitative indicators. Sustainability and ecological efficiency indicators have often been developed as ratios, such as water consumption to inhabitants, and amount of CO_2 produced per year.

A large amount of academic research is focused on the effort to implement weighting factor methods and techniques in the field of environment and sustainability in order to aggregate several indicators to obtain a single comprehensive index [62–65]. In general, four approaches have been followed to weight individual indicators: (a) using arbitrary (subjective) weights, *i.e.*, the same weights for all indicators; (b) generating weights from social preferences relative to different indicators that are associated to specific sustainability dimensions; (c) using expert judgment to build a set of weights; (d) generating weights endogenously from the dataset itself (for instance, by implementing non-parametric linear programming techniques or statistical analysis aimed at reducing the amount of variables), thus avoiding the introduction of any subjectivity linked to personal preferences.

When an arbitrary set of weights is utilized to aggregate individual indicators, the choice of one or more weights may not always be easily justified by a sound scientific argumentation because cities are very complex systems in which the interaction among sustainability policies, human behavior, infrastructure assets performance, resource use, *etc.* can be difficult to understand [66]. One common method that partially avoids arbitrariness in the selection of weights is the AHP method. Michael *et al.* [67] adopted AHP to rank and prioritize a set of urban sustainability indicators for Malaysia. Aldegheishem [68] evaluated the urban sustainable development for Riyadh city by implementing AHP. Specifically, 13 second-level sustainability indicators were grouped into three first-level indicators after generating weights by means of an analytical hierarchy process. By means of AHP, Hesari *et al.* [69] investigated the priorities of sustainable development components in improving the old fabrics of Isfahan city. However, weights generated by implementing AHP can be to a great extent subjective because they are provided by expert judgment. Moreover, when the number of indicators used is great, the involvement of experts and the process that generates weights can be time-consuming. Furthermore, even using AHP has the same drawbacks of all methods that choose subjective weights. One major problem is the replicability of the weighting set as it is very unlikely that different experts working independently would assign the same weights to all indicators [66].

Implementing statistical (parametric) methods and techniques allows obtaining objective weights, and, in some cases, determining to what extent an indicator's weight is approximately proportionate to the sustainability performance outcome. These methods include generally multivariate regression analysis, principal component analysis (PCA), and stochastic frontier analysis (SFA) [65]. Using data for OECD and non-OECD countries over a period of 20 years, Sengupta *et al.* [70] showed that the aggregation of sustainability indicators to form a unique index coupled with the implementation of multivariate statistical analysis provides important insights. Scholars showed that over the 20-year window some indicators have shifted in their importance in influencing the overall environmental index, while others have remained relatively irrelevant. Cuesta *et al.* [48] implemented a parametric stochastic method to calculate the distance from the environmental efficiency frontier. Even though these methods have the potential to provide robust results, limitations due to sample size and data availability make it impossible to estimate weights from data. DEA has become very popular as a non-parametric technique to measure environmental performance [71]. DEA has the advantage over other classification and ranking methods commonly used of its great flexibility in the generation of weights, ranging from a full objectivity to a large subjectivity. Indeed, weights can be generated either endogenously from data themselves, or taking into account the decision-maker judgment using various forms of restriction constraints added to the analysis. Zhou *et al.* [72] conducted an in-depth literature survey on the application of DEA to environment and energy studies. Zhou *et al.* [73] discussed the environmental DEA technologies that exhibit either non-increasing returns to scale or variable returns to scale. Zhou *et al.* [74] developed a non-radial DEA model and a non-radial Malmquist environmental efficiency to measure change of environmental performance of 26 OECD countries from 1995 to 1997. Two important advantages of DEA over parametric multivariate statistical methods are that it more easily accommodates both multiple inputs and multiple outputs, and it does not require any specific functional form to be imposed on the ecological efficiency model. Since its introduction, a large number of extensions to basic DEA models have appeared to deal with environmental-related benchmarking analyses. DEA has been especially implemented to evaluate cities' ecological efficiency. Cherchye and Kuosmanen [75] analyzed several DEA applications concerning country sustainability development. Lu and Lo [76] implemented DEA to rank 31 Chinese regions with respect to their sustainability. Wang *et al.* [47] adopted a meta-frontier function and a non-radial directional distance function to construct an index that at the same time calculates the performance achieved by coupling energy savings and emissions reductions. The method was used to evaluate energy-efficiency performance of 209 Chinese cities. Wang *et al.* [77] constructed three levels of regional eco-efficiency indicators by analyzing the flow of materials and implemented DEA to measure the eco-efficiency degree of Tongling City between 1990 and 2008. Huang *et al.* [78] proposed an extended DEA model that combines global benchmark technology, undesirable output, super efficiency and slacks-based measure to investigate the dynamics of regional eco-efficiency in China from 2000 to 2010. Üstün [79] used DEA to evaluate environmental efficiency of Turkish cities. The scholar evaluated the environmental efficiencies of 81 Turkish provinces in 2010 using four DEA models. Further, by using these measurements, he developed environmental efficiency maps of Turkey. The scholar employed the following inputs: total water resources, total environmental budget (*i.e.*, current expenditure and total environmental expenditure), and the following outputs: total amount of solid waste collected, number of people taken sewage service, number of people taken potable sewage service, the reciprocal of the maximum PM_{10} and SO_2 concentrations. Yin *et al.* [60] applied DEA to perform an eco-efficiency study of 30 Chinese provincial capital cities using environmental pollution as an undesirable output, and a modified super-efficiency model for ranking. Yu and Wen [80] utilized standard Banker-Charnes-Cooper (BCC) and Charnes-Cooper-Rhodes (CCR) DEA models and the Malmquist index to evaluate the status quo and future trends of 46 typical cities in China.

3. The Method

As mentioned earlier, the main goal of this study is to develop a method to compute a comprehensive index to measure the ecological efficiency of cities useful to generate rankings and conduct benchmarking analyses. The method assumes that individual cities can be stylized as (ecological) production functions that generate different outputs (*i.e.*, products and services) through the combination of a set of inputs. The household water consumption, the amount of households served by black water depuration plants, and the installed photovoltaic power are examples of outputs. Of course, in the perspective of the measurement of the city ecological efficiency, the outputs can be of different types, either good or bad. Thus, the household water consumption can be considered a bad output, while the number of photovoltaic power facilities installed on the roofs of public buildings and the number of households served by black water depuration are good outputs of the production function. The city administrators may adopt particular measures and policies to promote the diffusion of virtuous behaviors and best practices relative to sustainability among inhabitants, *i.e.*, the limitation or even the restriction of vehicle use in downtown areas, the adoption of no drive-days programs, the control of truck movements, a set of incentives to differentiate waste and recycling as annual fee reduction, *etc.* In order to produce outputs, cities have to consume a certain amount of resources. In general, the bigger the city size, the larger the amount of resource consumption will be. In general, both the size of the city territory and population are good proxies of the amount of the resources consumed by the city production process. One city can be more ecologically efficient than another city which has about the same population and territory extension if it produces a larger amount of good outputs, *i.e.*, the amount of differentiated and recycled waste, and a lower amount of bad outputs, *i.e.*, household electricity and water consumption.

Every city is associated with a specific production function that utilizes the same typologies of inputs and outputs. The capability of the city to generate the largest amount of good outputs as products and services that have a minimum impact on the environment and the lowest production of bad outputs that, *vice versa*, have a negative impact on environment with the same amount of inputs (population and territory area) is denominated ecological efficiency. Therefore, every city achieves a different ecological efficiency measurement as it has a different capability to generate good outputs limiting the production of bad outputs. Given this definition of ecological efficiency, a relative measurement of it can be obtained by implementing a non-parametric frontier approach based on DEA. DEA is a robust, standardized and transparent benchmarking technique [81–83], and literature has emphasized the advantages of using it to conduct efficiency analyses, in particular [83,84]: (a) it is an effective technique for measuring the efficiency of units in the presence of multiple outputs and multiple inputs; (b) it does not need any specific assumption relative to the type of production function to combine inputs and outputs; (c) it avoids introducing any subjective judgment or estimate in the analysis.

The proposed method to obtain a comprehensive measurement of the ecological efficiency of a city is developed in two steps: (1) the calculation of efficiency scores by implementing several DEA models adopting different perspectives; (2) the calculation of cross-efficiency scores; and (3) the combination of the efficiency scores by computing the Shannon's entropy index.

3.1. Step 1: the Calculation of the Individual Efficiency Scores

Since its first introduction in 1978, DEA has been widely adopted as a powerful and effective methodology for modeling operational processes of certain units that convert multiple inputs into multiple outputs and measuring their efficiency in order to conduct benchmarking studies [81]. As a non-parametric linear programming technique, DEA measures the efficiency of each unit (denominated DMU, Decision Making Unit) in a sample as the ratio of weighted outputs over weighted inputs. In particular, the efficiency of a DMU is measured relatively to similar DMUs with the goal to estimate the frontier that is associated to the best practice for the sample under evaluation. As Cooper *et al.* [82] claim, DEA is a technique that is aimed at measuring distances from efficient frontiers rather than at identifying central tendencies as it happens in statistical regression.

Assume that there is a set of n DMUs to be evaluated, and each DMU j (j = 1, ... ,n) produces s different outputs using m different inputs which are denoted as y_{rj} (r = 1, ... ,s) and x_{ij} (I = 1, ... ,m) respectively.

For any evaluated DMU k, the relative efficiency score is generally defined as the ratio of the weighted sum of outputs over the weighted sum of inputs, that is

$$E_{kk} = \frac{\sum\limits_{r=1}^{s} u_{rk} y_{rk}}{\sum\limits_{i=1}^{m} v_{ik} x_{ik}} \tag{1}$$

$v_k = (v_{1k}, \ldots ,v_{mk})$ and $u_k = (u_{1k}, \ldots ,u_{sk})$ are the input and output weighting vectors for the evaluation of DMU k, while u_{rk} and v_{ik} are respectively the multipliers of the outputs and the inputs.

Assuming an input orientation and that there is no constant proportionality between inputs and outputs along the efficient frontier, a measurement for the relative efficiency of DMU k can be obtained by solving the following multiplier model (the dual of the envelopment model) denoted as BCC DEA [85]:

$$\begin{gathered} \text{Max} \frac{\sum\limits_{r=1}^{s} u_{rk} y_{rk} + u_{*k}}{\sum\limits_{i=1}^{m} v_{ik} x_{ik}} \\ \text{s.t.} \quad \frac{\sum\limits_{r=1}^{s} u_{rk} y_{rj} + u_{*k}}{\sum\limits_{i=1}^{m} v_{ik} x_{ij}} \leqslant 1 \quad j = 1, ..., n \\ u_{rk}, v_{ik} \geqslant 0, \; u_{*k} \text{ free}, \quad r = 1, ..., s \quad \text{and} \quad i = 1, ..., m \end{gathered} \tag{2}$$

In this model, the variable u_{*k} is added to take into account different returns to scale along the efficient frontier.

A measurement for the relative efficiency of DMU k can be obtained by solving the following linear program, as follows [85]:

$$\begin{gathered}
\text{Max} \sum_{r=1}^{s} u_{rk} y_{rk} + u_{*k} \\
\text{s.t.} \quad \sum_{i=1}^{m} v_{ik} x_{ik} = 1 \\
\sum_{r=1}^{s} u_{rk} y_{rj} - \sum_{i=1}^{m} v_{ik} x_{ij} + u_{*k} \leqslant 0 \quad j = 1, \ldots, n \\
u_{rk} \geqslant 0, v_{ik} \geqslant 0, \ u_{*k} \text{ free}, \quad r = 1, \ldots, s \quad \text{and} \quad i = 1, \ldots, m
\end{gathered} \tag{3}$$

Model Equation (3) is solved n times, once for every DMU in the set. For each DMU k, a set of optimal input weights $v_{1k}{}^*, \ldots, v_{mk}{}^*$, and output weights $u_{1k}{}^*, \ldots, u_{sk}{}^*$ can be obtained by solving the above model Equation (3).

The ratio

$$E_{kk} = \frac{\sum_{r=1}^{s} u_{rk}^{*} y_{rk} + u_{*k}}{\sum_{i=1}^{m} v_{ik}^{*} x_{ik}} \tag{4}$$

is referred to as the BBC efficiency of DMU k when $u_k{}^*$ and $v_k{}^*$ are the optimal solution to model Equation (3). This measurement of efficiency reflects the self-evaluation of DMU k. $E_{kk} = 1$ if DMU k is 100% efficient, and $E_{kk} < 1$ if DMU k is inefficient.

3.2. Step 2: the Calculation of the Cross-Efficiency Scores

The common DEA models are unable to generate useful rankings across DMUs because more than one of them might be scored as 100% efficient by the mathematical programming algorithm. Additionally, because every DMU has its own set of weights, all of its weight might be assigned to a single output and input, making the efficiency analysis unrealistic. A promising approach to alleviate the weak discrimination capability of the basic DEA models is based on the calculation of the DMU cross-efficiency score [86]. While in the traditional DEA models the measurement of a DMU efficiency is based only on self evaluation, by assigning the most favorable set of weights for outputs and inputs to maximize its efficiency (that is to say, from an optimistic perspective), in the DEA cross-efficiency approach a peer evaluation together with a pure self evaluation of DMUs are performed [87]. Ranking procedures based on the calculation of cross-efficiency scores have a number of advantages [88,89]. Particularly, they do not need the introduction of unrealistic weighting schemes provided by expert judgment, and generate a unique DMU ranking to differentiate between good and poor performers. A DMU which achieves a high cross-efficiency score has been evaluated passing a more rigorous test, because it has been considered efficient by the majority of its peers and not only by itself. The method to calculate DMUs cross-efficiencies can be formulated as follows [86,90].

The cross-efficiency of each DMU j denominated as E_{kj} can be calculated using the optimal values of DMU k as follows:

$$E_{kj} = \frac{\sum_{r=1}^{s} u_{rk}^{*} y_{rj} + u_{*k}}{\sum_{i=1}^{m} v_{ik}^{*} x_{ij}} j \neq k \quad \text{and} \quad j = 1, \ldots, n. \tag{5}$$

These values are used to obtain an $n \times n$ cross-efficiency matrix, in which the diagonal entries show the conventional DEA efficiency scores of the DMUs (self evaluation) and the off-diagonal cells give the cross-efficiency scores (peer evaluation). In order to get the final efficiency score and a ranking of the DMUs, cross-efficiencies must be aggregated. Table 1 shows details. The average of cross-efficiencies is used as an aggregation method (average method).

When the DMU k multipliers are used to calculate the efficiency of the other DMUs in the cross-efficiency formulation, if u_{*k} is negative the expression $\sum_{r=1}^{s} u_{rk} y_{rj} + u_{*k}$ may be negative. Thus, in the input orientation approach the efficiency of DMU j may be negative when computed using the multipliers of DMU k. To avoid negative cross-efficiencies, Soares de Mello *et al.* [91] suggest adding the additional constraint $\sum_{r=1}^{s} u_{rk} y_{rj} + u_{*k} \geqslant 0$ in model (3).

The weights obtained from model (3) are usually not unique depending on the optimal solution arising from the particular LP software in use. Consequently, the cross-efficiency scores computed according to model (5) remain arbitrarily determined. To avoid such arbitrariness, secondary goals that optimize the input and output weights have been suggested in the literature [86,89,90].

Table 1. Cross-efficiency matrix for n DMUs and the calculation of cross-efficiency scores.

DMU	Target DMU			Average Cross-Efficiency
	1	2	n	
1	E_{11}	E_{12}	E_{1n}	$\frac{1}{n}\sum_{j=1}^{n} E_{1j}$
2	E_{21}	E_{22}	E_{2n}	$\frac{1}{n}\sum_{j=1}^{n} E_{2j}$
n	E_{n1}	E_{n2}	E_{nn}	$\frac{1}{n}\sum_{j=1}^{n} E_{nj}$

The most common goals are based on either an "aggressive" or a "benevolent" peer-evaluation of DMUs. In the aggressive approach, the mean of efficiencies of the other DMUs is minimized in order to maximize the self-efficiency of the DMU under evaluation. The aim of the aggressive approach is to find optimal weights that make the evaluated DMU look the best that it can be and the remaining *n-1* DMUs worse. In the benevolent approach, not only the efficiency of the evaluated DMU is maximized but also the mean efficiency of the remaining DMUs. In this formulation, the aim is to obtain weights that make both the DMU under evaluation and the remaining *n-1* DMUs look as good as possible.

The aggressive evaluation DEA cross-efficiency model is formulated as follows

$$\begin{gathered}
\min \quad \sum_{r=1}^{s} u_{rk} \left(\sum_{j=1, j \neq k}^{n} y_{rj} \right) + u_{*k} \\
\text{s.t.} \quad \sum_{i=1}^{m} v_{ik} \left(\sum_{j=1, j \neq k}^{n} x_{ij} \right) = 1 \\
\sum_{r=1}^{s} u_{rk} y_{rk} - E_{kk}^{*} \sum_{i=1}^{m} v_{ik} x_{ik} + u_{*k} = 0 \quad j \neq k, j = 1, \ldots, n \\
\sum_{r=1}^{s} u_{rk} y_{rj} - \sum_{i=1}^{m} v_{ik} x_{ij} + u_{*k} \leqslant 0 \\
u_{rk} \geqslant 0,\ v_{ij} \geqslant 0,\ u_{*k} \text{ free}, \quad r = 1, \ldots, s, \quad i = 1, \ldots, m
\end{gathered} \tag{6}$$

$E_{kk}{}^{*}$ is the optimal BCC self-evaluation of DMU k.

In the benevolent evaluation DEA cross-efficiency model, the objective function of model Equation (6) is changed from minimizing to maximizing.

3.3. Step 3: the Aggregation of Different DEA Efficiency Scores Using the Shannon's Entropy Index

In order to have a more comprehensive evaluation of the city ecological efficiency, the suggested method calculates the cross-efficiency measurements from different perspectives and approaches, running several DEA models. Even performing cross-efficiency analysis, any single DEA model has limited discriminatory power to generate an effective ranking of cities and, henceforth, it is useful to combine the results provided by several models integrating the different rankings of DMUs.

Thus, to have a comprehensive measurement for the efficiencies, which takes into account various perspectives and approaches at the same time, the Shannon-DEA procedure as implemented by Bian and Yang [92] is adopted. This procedure is based on the calculation of the Shannon's entropy index that is used as a coefficient of importance degree [93,94]. Several scholars have showed that this comprehensive efficiency index discriminates better than individual DEA models to rank DMUs [92,94–96]. Furthermore, the aggregation based on the Shannon's entropy index of different efficiency measurements is better than the aggregation performed averaging the efficiency scores because it provides a Pareto optimal solution.

Bian and Yang [92] suggest a procedure that is based on six steps:

(1) Generation of an $n \times q$ efficiency matrix E where n is the number of DMUs and q is the number of different DEA models performed. In matrix E, each row corresponds to a DMU and each column corresponds to a DEA cross-efficiency evaluation model. Therefore, as an example, CE_{22} is the cross-efficiency score of DMU 2 obtained by performing DEA model 2.

(2) Normalization of the efficiency matrix E recalculating the individual efficiencies as $e_{jp} = E_{jp}/\sum_{j=1}^{n} E_{jp}$ ($p = 1, \ldots, q$ and $j = 1, \ldots, n$)

(3) Calculation of the Shannon's entropy index H_p for each DEA model p as $H_p = -(\ln n)^{-1}\sum_{j=1}^{n} e_{jp}\ln(e_{jp})$ ($p = 1, \ldots, q$ and $j = 1, \ldots, n$)

(4) Calculation of the diversification degree for every DEA model as $d_p = 1\text{-}H_p$ ($p = 1, \ldots, q$). The greater d_p, the greater the discriminatory power of the DEA model p. If a DEA model yields approximately equal efficiency scores for all DMUs, the DEA model has no discrimination ability for those DMUs, and the resulting d_p has a small degree of importance. Accordingly, we can use d_p to rate the importance of model p.

(5) Assessment of the importance degree of model p by calculating the weights of every DEA model using $w_p = d_p/\sum_{p=1}^{q} d_p$ ($p = 1, \ldots, q$) where $\sum_{p=1}^{q} w_p = 1$

(6) Calculation of the cross-efficiency comprehensive index of DMU j as $XECI_j = \sum_{p=1}^{q} w_p E_{jp}$ ($j = 1, \ldots, n$).

	DEA Model 1	**DEA Model 2**	**DEA Model q**
DMU *1*	CE_{11}	CE_{12}	CE_{1q}
DMU *2*	CE_{21}	CE_{22}	CE_{2q}
DMU *n*	CE_{n1}	CE_{n2}	CE_{nq}

4. Case Study

The method for the calculation of the ecological efficiency index was used to perform a benchmarking study aimed at ranking and comparing Italian Province capital cities. The method was applied in two steps. In the first step, individual rankings were obtained by implementing seven DEA models, one calculating conventional DEA efficiency, and the remaining ones calculating cross-efficiency. In the second step, the six cross-efficiency models were combined together to get a single ranking by means of the Shannon's entropy index. Finally, results were compared with the ranking provided by Sole24Ore in 2011. This particular year was chosen because of data availability and reliability. The purpose of this comparison is not to identify the better ranking but rather to test the performance of the proposed method in terms of its discrimination capability. Indeed, relative rankings are generally influenced not only by the dataset, but also by the variables used in the model and the ranking methodology [97].

4.1. Sample

Italy is the fifth manufacturing economy in the world, with a population of about 57 million people that are concentrated on a relatively small territory. The intense industrial development on one side, and the high population density on the other side have lead to a strong environmental pressure making the environmental protection an important public concern. Even though much environmental progress has been achieved in the last decade, air pollution, traffic congestion, waste production, and excessive resource consumption still remain major problems.

In Italy, urban areas, and particularly cities and towns, have become very important to support policy actions aimed at improving environment quality. The Bassanini Act issued in 1997 strengthened the competence of local authorities as to environmental issues management. However, there are remarkable disparities across cities with respect to the capability of local governments to modify resource consumption patterns, waste management approaches, and the determinants of urban mobility towards more sustainable paths.

This study considers Italian Province capital cities as units of analysis. However, because of data unavailability, and missing values indeed being a major problem when DEA is performed, the sample size is limited to 116 capital cities.

4.2. DEA Models

Several DEA models were implemented to compute cross-efficiencies from different perspectives (*i.e.*, arbitrary, aggressive and benevolent) as different models lead to different cross-efficiency scores. For all models, both input and output-orientations were chosen. In total, seven DEA models were performed. The assumption of variable returns to scale (VRS) was made because of the large variety of cities in terms of population and land area sizes, henceforth adopting the approach suggested by Banker *et al.* [85].

The first model (Model A) implemented conventional VRS DEA to evaluate cities ecological efficiencies. The other 6 models (Model A to Model G) implemented VRS cross-efficiency DEA and generated preliminary rankings of cities with respect to their ecological efficiency. Table 2 shows the DEA models adopted to carry on the study.

Table 2. Description of data envelopment analysis (DEA) models.

Model	Model Type	Orientation	Weight Computation	Approach
Model A	conventional	output-oriented	1 stage	-
Model B	cross-efficiency	output-oriented	1 stage	arbitrary
Model C	cross-efficiency	input-oriented	1 stage	arbitrary
Model D	cross-efficiency	output-oriented	2 stage (secondary goal)	benevolent
Model E	cross-efficiency	output-oriented	2 stage (secondary goal)	aggressive
Model F	cross-efficiency	input-oriented	2 stage (secondary goal)	benevolent
Model G	cross-efficiency	input-oriented	2 stage (secondary goal)	aggressive

4.3. Variables

Table 3 presents input and output variables used in the study to implement DEA models. As Thanassoulis [98] claims, the identification of input and output variables in DEA applications is both difficult and crucial. Thus, variables were identified having clearly in mind the purpose of the study and similar studies. However, as is common in studies like this, the selection of variables was influenced by data availability. Two inputs used in the analysis—the city population and territory land area—have been considered as non-discretionary or uncontrollable variables because they are not under control of the productive unit (*i.e.*, the Province capital city), and cannot be controlled by the city council administrators (see, for instance, [99]). Even though the total city population and land area have been considered as uncontrollable variables in DEA models that cannot be controlled by the city decision makers, they are internal to the city production process. As these inputs are assumed to be part of the production process, they contribute to define the production possibility set (PPS) and the efficient frontier together with the discretionary inputs and the outputs. These production factors have been included in the models as suggested in the literature [100]. The uncontrollable inputs do not enter directly in the efficiency measures being optimized in the objective function of the DEA model. However, they can affect the efficiency measurements because of their inclusion in the constraints (see Appendix).

Outputs are classified as either being "good" or "bad", whether they are desirable or undesirable. Because undesirable outputs are jointly produced with desirable outputs, as Yang and Pollit [101] (p. 1096) suggest: "[...] *it makes sense for us to credit a DMU for its provision of desirable outputs and to penalize it for its production of emissions when evaluating its performance*". In the presence of undesirable outputs, the DMUs having a larger amount of good (desirable) outputs and a lower amount of bad (undesirable) outputs relative to fewer inputs should be regarded as efficient [82]. Undesirable outputs were treated as inputs in the DEA models following literature [101–105]. Additionally, including the undesirable outputs as inputs in the DEA model is consistent with the measure of eco-efficiency indicated by the World Council for Sustainable Business Development as the ratio of the product/service value to the environmental influence [106].

Measurements for the variables were collected from the ISTAT database. Since 1996, ISTAT collects data relative to major Italian cities. The environmental issues investigated refer to the main following themes—air, energy, green areas, noise, transport, waste and water. Data relative to year 2011 have been used to calculate the city ecological efficiency index. In total, two inputs and 12 outputs (six desirable and six undesirable included as six further inputs) have been considered in the analysis.

Table 3. Input and output variables.

Variable	Type	Classified as	Description
DEPURATION	output	good	amount of inhabitants living in the province capital city served by black water depuration service (year 2011)
DWASTE	output	good	amount of differentiated urban waste collected in the province capital city (kg) (year 2011)
PHOTOVOLTAICS	output	good	total power of photovoltaic plants installed on public building roofs (kW) (year 2011)
GREEN	output	good	total amount of urban green available to citizens (square m) (year 2011)
TRANSPORTATION	output	good	demand for public transportation (no. of passengers) (year 2011)
NPCARS	output	good	no. of cars owned by people living in the province capital city classified as euro IV and euro V (year 2011)
WATER	output	bad	household water consumption (liters per day) (year 2011)
NDWASTE	output	bad	amount of not differentiated urban waste collected (kg) (year 2011)
GAS	output	bad	household natural gas consumption (cooking and heating) (cubic meters) (year 2011)
ELECTRICITY	output	bad	household electricity consumption (kWh) (year 2011)
POLLUTION	output	bad	exceedance days of air quality threshold value of PM10 (year 2011)
PCARS	output	bad	no. of cars owned by people living in the province capital city classified as euro 0–III (polluting cars) (year 2011)
POPULATION	input	non discretionary	total population living in the province capital city (year 2011)
AREA	input	non discretionary	total city land area (squared km) (year 2011)

4.4. Results

Table 4 displays efficiency scores calculated by implementing DEA Models A–G, the efficiency score computed as a comprehensive measurement by using the Shannon's entropy index (XECI), and the measurements relative to environmental quality used by Sole24Ore to construct the city livability index. Additionally, Table 4 shows the ranking levels of cities for every model, too. As it has been emphasized in the second section of this paper, the Sole24Ore index has a large amount of subjectivity determined by the arbitrary choice of the set of weights utilized to combine and group 25 indicators of environmental quality into seven macro-indicators that are finally aggregated to get an individual index of environmental quality by adopting a further set of weights. For instance, for the aggregation of the depuration, water consumption, and water dispersion indicators related to the water macro-indicator, the weights of six, 3.5 and 2.5 are adopted. Moreover, the indicators are normalized by using certain utility functions that are developed taking into account some sustainability goals. In this way, scores given to indicators provide a measurement of the sustainability rate of a city when it is compared to an ideal city.

Model A has 70 full (100%) efficient cities and a large number of cities having their efficiency scores higher than 90%. Efficiencies are between 51.6% and 100%, while mean efficiency is 96.5%, and standard deviation is only 7.4%. Model A thus remains useless to rank cities with respect to their ecological efficiency because of its scarce discrimination power. On the contrary, models from Model A to Model G which are based on the computation of the cross-efficiency score offer a better discriminatory power. Indeed, the minimum efficiency score decreases from 51.6% (Model A) to 7.0% (Model D), and is never higher than 13.5% (Model G). These models have a higher standard deviation measurement than Model A, confirming their greater discriminatory capability. The analysis of the ranking levels emerging from the cross-efficiency calculation supports the idea that Model A is the worst one. Indeed, this model is able to identify only 39 ranks. The adoption of the cross-efficiency method largely increases the number of ranking levels. The model that calculates ecological efficiency by utilizing the Shannon's entropy index (XECI model) behaves slightly better than the previous DEA cross-efficiency models, as it identifies 103 ranks. This model behaves even better than the index computed by the Sole24Ore which identifies only 90 ranking levels while covers 107 cities. Thus, there is no indication that the ranking provided by the Sole24Ore is particularly discriminating.

According to the XECI model, mean ecological efficiency relative to cities in sample is 60.91%, the maximum efficiency is 84.21% and the minimum efficiency is only 11.05%. Forty-seven cities achieve an ecological efficiency score which is below average. Moreover, among cities that are placed in the first 10 positions of the ranking, four of them are located in the North of Italy (Aosta, Genova, Milano and Trento), three in the Center of Italy (Livorno, Prato and Roma), two in the Isles (Oristano and Tortolì) and only one in the South (Salerno), even though this latter achieves the higher level in the ranking with the score of 84.21%. These results are not unexpected. Indeed, in the last decade Salerno has become one of the excellent and more livable cities in Southern Italy. Since 2006, the local government has implemented a well-organized and efficient solid waste management, with the doorstep collection of waste, a high rate of recycling, and a strong involvement of the population. In addition, since the middle of the 90s, the city administration has largely invested to improve urban quality and increase the attractiveness of the city internationally. The local governments of Aosta, Genova, Milano and Trento have also adopted good practices to improve the quality of environment and sustainability. They all approved the Plan for Green and/or have implemented Local Agenda 21, while Milano, Trento and Genova implemented the Urban Mobility and Logistics Plan and an Infomobility System aimed at reducing traffic congestion. Trento made a great effort to support the installation of renewable solar facilities and the usage of public transportation, particularly by public employees going at work. Even though the city of Milano did a limited investment to install renewable energy plants on the roofs of public buildings, the local government promoted the adoption of design methods and construction materials improving energy efficiency of public and private buildings. This practice allowed having an important reduction of natural gas consumption.

Table 4. Efficiency scores.

DMU	Province Capital Cities	Model A		Model B		Model C		Model D		Model E		Model F		Model G		XECI		Sole24Ore	
		Eff	Rank	Eff	Rank	Eff	Rank	Eff	Rank	Eff	Rank	Eff	Rank	Eff	Rank	Eff	Rank	Index	Rank
CI1	Agrigento	0.884	26	0.338	90	0.391	92	0.532	86	0.303	91	0.477	93	0.382	90	0.4027	97	0.327	75
CI2	Alessandria	0.865	30	0.472	77	0.513	79	0.737	68	0.423	78	0.639	74	0.521	77	0.5497	83	0.462	54
CI3	Ancona	0.975	12	0.565	40	0.630	35	0.851	29	0.507	40	0.781	22	0.633	32	0.6597	34	0.527	33
CI4	Andria	1.000	1	0.535	52	0.627	36	0.833	36	0.469	61	0.762	32	0.597	45	0.6355	43	-	-
CI5	Aosta	1.000	1	0.740	3	0.816	3	0.980	1	0.719	2	0.958	1	0.829	1	0.8391	2	0.593	14
CI6	Arezzo	0.869	29	0.461	80	0.519	77	0.695	76	0.394	83	0.629	77	0.506	77	0.5324	86	0.449	59
CI7	Ascoli Piceno	0.950	17	0.473	76	0.527	74	0.776	60	0.422	79	0.661	65	0.531	73	0.5638	78	0.537	30
CI8	Asti	0.989	7	0.526	56	0.566	60	0.832	37	0.479	57	0.713	47	0.578	54	0.6144	57	0.447	61
CI9	Avellino	1.000	1	0.591	28	0.665	26	0.881	16	0.575	22	0.828	10	0.674	23	0.7012	21	0.448	60
CI10	Bari	1.000	1	0.669	11	0.693	18	0.892	12	0.605	10	0.796	20	0.688	16	0.7230	15	0.442	65
CI11	Barletta	1.000	1	0.574	36	0.677	23	0.861	24	0.509	38	0.819	14	0.657	25	0.6811	28	-	-
CI12	Belluno	1.000	1	0.365	88	0.422	90	0.470	90	0.303	91	0.481	92	0.413	88	0.4078	95	0.693	2
CI13	Benevento	0.833	33	0.198	95	0.212	97	0.224	95	0.176	96	0.249	99	0.219	94	0.2124	102	0.507	40
CI14	Bergamo	1.000	1	0.576	35	0.598	47	0.856	26	0.549	28	0.722	44	0.615	39	0.6516	36	0.521	35
CI15	Biella	0.992	4	0.515	62	0.546	69	0.825	41	0.487	52	0.684	58	0.568	58	0.6029	61	0.468	52
CI16	Bologna	1.000	1	0.661	14	0.694	17	0.898	10	0.604	11	0.822	12	0.688	16	0.7267	13	0.600	11
CI17	Bolzano	1.000	1	0.651	17	0.702	14	0.891	13	0.593	18	0.811	17	0.704	13	0.7240	14	0.666	4
CI18	Brescia	1.000	1	0.641	18	0.682	21	0.907	8	0.585	21	0.813	16	0.683	18	0.7173	18	0.496	43
CI19	Brindisi	1.000	1	0.570	38	0.655	29	0.854	27	0.492	48	0.781	22	0.627	34	0.6612	33	0.445	63
CI20	Cagliari	1.000	1	0.640	19	0.664	27	0.895	11	0.588	20	0.762	32	0.657	25	0.7002	22	0.496	43
CI21	Caltanissetta	0.760	36	0.371	87	0.412	91	0.612	84	0.327	89	0.500	91	0.401	89	0.4362	93	0.321	76
CI22	Campobasso	1.000	1	0.480	74	0.565	61	0.784	58	0.435	74	0.698	53	0.567	59	0.5864	69	0.499	42
CI23	Carbonia	1.000	1	0.718	7	0.791	5	0.779	59	0.597	16	0.757	35	0.746	9	0.7295	12	0.496	43
CI24	Caserta	1.000	1	0.608	24	0.677	23	0.879	17	0.555	27	0.804	19	0.676	21	0.6983	23	0.476	50
CI25	Catania	1.000	1	0.250	94	0.215	96	0.244	94	0.197	95	0.206	100	0.215	95	0.2210	101	0.286	81
CI26	Catanzaro	1.000	1	0.499	71	0.513	79	0.668	81	0.459	65	0.559	88	0.511	76	0.5343	85	0.307	79
CI27	Chieti	0.796	35	0.500	70	0.545	70	0.705	73	0.442	72	0.629	77	0.551	66	0.5606	79	0.540	28
CI28	Como	0.993	3	0.534	53	0.554	67	0.829	38	0.508	39	0.678	61	0.574	55	0.6119	58	0.459	57
CI29	Cosenza	0.942	18	0.477	75	0.532	72	0.759	65	0.453	66	0.668	64	0.539	71	0.5701	73	0.424	68
CI30	Cremona	0.990	6	0.507	66	0.532	72	0.816	44	0.471	60	0.657	68	0.551	66	0.5878	67	0.517	36
CI31	Crotone	0.914	23	0.460	81	0.513	79	0.721	71	0.407	81	0.598	83	0.503	79	0.5322	86	0.232	87
CI32	Cuneo	0.959	15	0.547	46	0.607	44	0.826	40	0.480	56	0.734	40	0.610	41	0.6322	46	0.589	15
CI33	Enna	0.698	38	0.305	92	0.350	93	0.531	87	0.272	93	0.421	95	0.338	91	0.3687	98	0.278	82
CI34	Fermo	0.935	20	0.471	78	0.524	76	0.762	64	0.418	80	0.643	72	0.530	74	0.5565	81	-	-
CI35	Ferrara	0.877	27	0.532	54	0.560	63	0.770	62	0.452	67	0.658	67	0.559	62	0.5872	68	0.562	21

Table 4. *Cont.*

DMU	Province Capital Cities	Model A		Model B		Model C		Model D		Model E		Model F		Model G		XECI		Sole24Ore	
		Eff	Rank	Eff	Rank	Eff	Rank	Eff	Rank	Eff	Rank	Eff	Rank	Eff	Rank	Eff	Rank	Index	Rank
CI36	Firenze	1.000	1	0.567	39	0.591	51	0.702	74	0.520	35	0.687	57	0.587	51	0.6080	60	0.509	39
CI37	Foggia	1.000	1	0.543	48	0.624	37	0.834	35	0.475	59	0.751	37	0.589	50	0.6347	44	0.460	56
CI38	Forlì	1.000	1	0.585	32	0.627	36	0.803	50	0.500	45	0.734	40	0.627	34	0.6444	41	0.595	13
CI39	Frosinone	0.844	32	0.397	85	0.422	90	0.678	80	0.380	84	0.563	87	0.438	86	0.4789	89	0.273	83
CI40	Genova	1.000	1	0.694	9	0.721	11	0.891	13	0.621	9	0.839	9	0.710	10	0.7448	9	0.570	19
CI41	Gorizia	0.935	20	0.536	51	0.592	50	0.772	61	0.499	46	0.710	48	0.608	42	0.6179	54	0.533	32
CI42	Grosseto	1.000	1	0.628	21	0.671	24	0.858	25	0.526	32	0.757	35	0.630	33	0.6772	29	0.445	63
CI43	Iglesias	1.000	1	0.398	84	0.476	85	0.569	85	0.362	87	0.519	89	0.465	81	0.4636	92	0.496	43
CI44	Imperia	0.516	39	0.115	96	0.130	98	0.070	96	0.099	97	0.116	101	0.135	96	0.1105	103	0.314	77
CI45	Isernia	1.000	1	0.477	75	0.562	62	0.719	72	0.460	64	0.620	80	0.552	65	0.5639	78	0.312	78
CI46	La Spezia	1.000	1	0.610	23	0.693	18	0.825	41	0.549	28	0.806	18	0.681	19	0.6922	26	0.636	5
CI47	Lanusei	1.000	1	0.514	63	0.645	31	0.784	58	0.488	51	0.697	54	0.644	29	0.6268	49	-	-
CI48	L'Aquila	1.000	1	0.583	33	0.609	43	0.692	77	0.479	57	0.735	39	0.572	56	0.6104	59	0.365	72
CI49	Latina	0.979	10	0.560	42	0.599	46	0.844	31	0.486	53	0.715	46	0.593	49	0.6315	47	0.289	80
CI50	Lecce	0.980	9	0.485	73	0.525	75	0.799	52	0.430	76	0.643	72	0.523	76	0.5662	76	0.448	60
CI51	Lecco	0.999	2	0.520	59	0.569	59	0.826	40	0.483	55	0.698	53	0.586	52	0.6123	58	0.441	66
CI52	Livorno	1.000	1	0.723	6	0.789	6	0.920	6	0.634	6	0.905	6	0.766	8	0.7877	6	0.537	30
CI53	Lodi	1.000	1	0.502	69	0.518	78	0.794	54	0.485	54	0.641	73	0.541	70	0.5794	71	0.568	20
CI54	Lucca	0.874	28	0.507	66	0.541	71	0.736	69	0.443	71	0.643	72	0.549	68	0.5685	75	0.545	27
CI55	Macerata	0.731	37	0.396	86	0.448	88	0.621	83	0.359	88	0.564	86	0.455	83	0.4725	90	0.584	16
CI56	Mantova	1.000	1	0.477	75	0.494	81	0.799	52	0.446	69	0.630	76	0.517	74	0.5596	80	0.595	13
CI57	Massa	0.940	19	0.557	44	0.590	52	0.803	50	0.485	54	0.672	63	0.594	48	0.6153	56	0.307	79
CI58	Matera	1.000	1	0.696	8	0.695	16	0.875	19	0.601	13	0.780	23	0.679	20	0.7202	17	0.448	60
CI59	Messina	1.000	1	0.595	27	0.594	49	0.789	55	0.532	30	0.649	71	0.589	50	0.6238	50	0.162	90
CI60	Milano	1.000	1	0.773	2	0.796	4	0.948	4	0.699	3	0.910	5	0.769	7	0.8149	3	0.501	41
CI61	Modena	1.000	1	0.628	21	0.666	25	0.895	11	0.558	25	0.795	21	0.671	24	0.7006	21	0.527	33
CI62	Monza	1.000	1	0.596	26	0.632	34	0.872	21	0.593	18	0.777	25	0.647	28	0.6853	27	-	-
CI63	Napoli	1.000	1	0.652	16	0.665	26	0.828	39	0.603	12	0.760	34	0.654	27	0.6929	25	0.360	73
CI64	Novara	1.000	1	0.581	34	0.612	42	0.838	34	0.522	33	0.731	41	0.623	35	0.6499	37	0.445	63
CI65	Nuoro	1.000	1	0.473	76	0.480	84	0.409	91	0.376	85	0.407	96	0.442	85	0.4305	94	0.554	25
CI66	Olbia	1.000	1	0.576	35	0.597	48	0.819	42	0.492	48	0.655	69	0.594	48	0.6207	52	0.515	37
CI67	Oristano	1.000	1	0.672	10	0.779	8	0.891	13	0.600	14	0.871	7	0.770	6	0.7616	8	0.525	34
CI68	Padova	1.000	1	0.633	20	0.644	32	0.865	23	0.603	12	0.773	27	0.654	27	0.6945	24	0.535	31
CI69	Palermo	1.000	1	0.327	91	0.322	94	0.394	92	0.290	92	0.359	97	0.319	92	0.3350	99	0.235	86
CI70	Parma	1.000	1	0.567	39	0.622	38	0.851	29	0.498	47	0.761	33	0.622	36	0.6518	36	0.619	8
CI71	Pavia	0.975	12	0.477	75	0.493	82	0.786	56	0.440	73	0.610	81	0.512	75	0.5520	82	0.485	48
CI72	Perugia	0.959	15	0.608	24	0.647	30	0.839	33	0.506	41	0.764	30	0.630	33	0.6643	31	0.615	9

Table 4. *Cont.*

DMU	Province Capital Cities	Model A		Model B		Model C		Model D		Model E		Model F		Model G		XECI		Sole24Ore	
		Eff	Rank	Eff	Rank	Eff	Rank	Eff	Rank	Eff	Rank	Eff	Rank	Eff	Rank	Eff	Rank	Index	Rank
CI73	Pesaro	0.874	28	0.558	43	0.598	46	0.779	59	0.489	50	0.702	51	0.602	43	0.6198	53	0.561	22
CI74	Pescara	0.988	8	0.517	61	0.548	68	0.753	67	0.503	44	0.661	65	0.556	63	0.5887	66	0.425	67
CI75	Piacenza	0.991	5	0.590	29	0.624	37	0.868	22	0.529	31	0.745	38	0.636	31	0.6641	31	0.538	29
CI76	Pisa	0.814	34	0.471	78	0.499	80	0.699	75	0.405	82	0.586	84	0.504	78	0.5259	87	0.596	12
CI77	Pistoia	1.000	1	0.468	79	0.472	86	0.530	88	0.394	83	0.514	90	0.448	84	0.4701	91	0.457	58
CI78	Pordenone	1.000	1	0.522	57	0.529	73	0.654	82	0.520	35	0.623	79	0.550	67	0.5659	77	0.620	7
CI79	Potenza	1.000	1	0.587	30	0.615	40	0.826	40	0.517	36	0.717	45	0.619	37	0.6455	39	0.461	55
CI80	Prato	1.000	1	0.724	5	0.787	7	0.949	3	0.656	4	0.929	2	0.776	5	0.8018	4	0.537	30
CI81	Ragusa	0.990	6	0.513	64	0.571	57	0.809	46	0.448	68	0.682	60	0.548	69	0.5938	64	0.446	62
CI82	Ravenna	1.000	1	0.571	37	0.580	55	0.828	39	0.478	58	0.675	62	0.583	53	0.6178	54	0.557	23
CI83	Reggio Calabria	1.000	1	0.564	41	0.570	58	0.754	66	0.492	48	0.626	78	0.566	60	0.5945	64	0.222	88
CI84	Reggio Emilia	1.000	1	0.601	25	0.647	30	0.806	48	0.521	34	0.763	31	0.644	29	0.6621	32	0.605	10
CI85	Rieti	0.852	31	0.412	83	0.460	87	0.684	79	0.362	86	0.571	85	0.456	82	0.4896	88	0.513	38
CI86	Rimini	1.000	1	0.665	13	0.699	15	0.916	7	0.591	19	0.820	13	0.708	11	0.7317	11	0.556	24
CI87	Roma	1.000	1	0.740	3	0.705	13	0.887	14	0.656	4	0.779	24	0.685	17	0.7416	10	0.457	58
CI88	Rovigo	0.952	16	0.503	68	0.545	70	0.789	55	0.465	62	0.683	59	0.564	61	0.5904	65	0.367	71
CI89	Salerno	1.000	1	0.816	1	0.820	2	0.963	2	0.732	1	0.911	4	0.817	3	0.8421	1	0.473	51
CI90	Sanluri	1.000	1	0.544	47	0.723	10	0.804	49	0.490	49	0.755	36	0.694	15	0.6657	30	-	-
CI91	Sassari	1.000	1	0.733	4	0.735	9	0.851	29	0.599	15	0.761	33	0.671	24	0.7241	14	0.515	37
CI92	Savona	0.980	9	0.517	61	0.597	48	0.817	43	0.464	63	0.725	42	0.593	49	0.6172	55	0.556	24
CI93	Siena	1.000	1	0.665	13	0.720	12	0.884	15	0.556	26	0.811	17	0.700	14	0.7211	16	0.488	47
CI94	Siracusa	1.000	1	0.455	82	0.488	83	0.800	51	0.425	77	0.637	75	0.490	80	0.5482	84	0.262	84
CI95	Sondrio	1.000	1	0.542	49	0.570	58	0.826	40	0.569	24	0.703	50	0.598	44	0.6340	45	0.582	17
CI96	Taranto	0.907	24	0.487	72	0.545	70	0.763	63	0.433	75	0.660	66	0.534	72	0.5689	74	0.357	74
CI97	Tempio Pausania	1.000	1	0.347	89	0.437	89	0.498	89	0.305	90	0.445	94	0.422	87	0.4075	96	0.515	37
CI98	Teramo	0.999	2	0.556	45	0.616	39	0.840	32	0.487	52	0.745	38	0.615	39	0.6412	42	0.490	46
CI99	Terni	0.905	25	0.521	58	0.569	59	0.785	57	0.460	64	0.706	49	0.572	56	0.6005	62	0.547	26
CI100	Torino	1.000	1	0.669	11	0.659	28	0.901	9	0.633	7	0.772	28	0.671	24	0.7169	18	0.495	44
CI101	Tortolì	1.000	1	0.668	12	0.839	1	0.874	20	0.655	5	0.852	8	0.819	2	0.7824	7	-	-
CI102	Trani	1.000	1	0.518	60	0.602	45	0.826	40	0.464	63	0.735	39	0.596	46	0.6218	51	-	-

Table 4. *Cont.*

DMU	Province Capital Cities	Model A		Model B		Model C		Model D		Model E		Model F		Model G		XECI		Sole24Ore	
		Eff	Rank	Eff	Rank	Eff	Rank	Eff	Rank	Eff	Rank	Eff	Rank	Eff	Rank	Eff	Rank	Index	Rank
CI103	Trapani	0.918	22	0.511	65	0.559	64	0.723	70	0.443	71	0.609	82	0.526	75	0.5605	79	0.240	85
CI104	Trento	1.000	1	0.733	4	0.787	7	0.940	5	0.631	8	0.928	3	0.784	4	0.7985	5	0.682	3
CI105	Treviso	0.928	21	0.272	93	0.275	95	0.318	93	0.261	94	0.311	98	0.290	93	0.2878	100	0.465	53
CI106	Trieste	0.972	13	0.564	41	0.614	41	0.840	32	0.505	42	0.745	38	0.611	40	0.6451	40	0.492	45
CI107	Udine	1.000	1	0.586	31	0.594	49	0.838	34	0.538	29	0.695	55	0.617	38	0.6438	41	0.577	18
CI108	Varese	1.000	1	0.544	47	0.577	56	0.845	30	0.504	43	0.701	52	0.595	47	0.6265	49	0.410	70
CI109	Venezia	1.000	1	0.514	63	0.581	54	0.690	78	0.422	79	0.701	52	0.553	64	0.5754	72	0.635	6
CI110	Verbania	1.000	1	0.612	22	0.689	19	0.876	18	0.574	23	0.816	15	0.706	12	0.7107	20	0.737	1
CI111	Vercelli	0.991	5	0.506	67	0.556	66	0.815	45	0.460	64	0.693	56	0.570	57	0.5983	63	0.444	64
CI112	Verona	1.000	1	0.653	15	0.679	22	0.853	28	0.595	17	0.826	11	0.675	22	0.7126	19	0.507	40
CI113	Vibo Valentia	1.000	1	0.530	55	0.643	33	0.828	39	0.490	49	0.775	26	0.640	30	0.6492	38	0.208	89
CI114	Vicenza	0.969	14	0.547	46	0.588	53	0.807	47	0.512	37	0.724	43	0.602	43	0.6289	48	0.479	49
CI115	Villacidro	1.000	1	0.537	50	0.688	20	0.809	46	0.478	58	0.769	29	0.656	26	0.6538	35	-	-
CI116	Viterbo	0.978	11	0.514	63	0.557	65	0.795	53	0.445	70	0.650	70	0.534	72	0.5812	70	0.414	69
	max	1.000		0.816		0.839		0.980		0.732		0.958		0.829		0.8421		0.737	
	min	0.516		0.115		0.130		0.070		0.099		0.116		0.135		0.1105		0.162	
	mean	0.965		0.542		0.587		0.772		0.487		0.689		0.584		0.6091		0.476	
	st.dev	0.074		0.116		0.123		0.153		0.106		0.142		0.119		0.1228		0.115	

Focusing on the latest 10 positions in the ranking, six cities are located in the isles (Catania, Enna, Nuoro, Palermo, Tempio Pausania), three in the North (Belluno, Imperia, Treviso), and one in the South of Italy (Benevento). In 2011, the small city of Benevento achieved important environmental targets, *i.e.*, an acceptable rate of differentiated waste collection, an average production of solid waste per inhabitant of about 400 kg and moderate electricity consumption, but it suffered from high levels of pollution in terms of concentration of PM_{10} and scarce water treatment. Black water treatment still remains a major problem for many cities in the isles, too.

Table 5 presents information relative to the importance degrees utilized to compute the comprehensive ecological efficiency index for sample cities. Data show that Model E has the highest (0.17721) importance degree (W_p), and, as a consequence, the ranking generated by Model E can be adopted as an acceptable substitute to the ranking obtained by calculating XECI. Model E has also the highest diversification degree (d_p) measurement. Model G has both low importance and diversification degrees measurements and offers an unacceptable discriminatory capability to generate useful rankings.

The Pearson correlations and the Spearman's rank correlations have been calculated to assess the sensitivity of rankings to the particular DEA model (see Tables 6 and 7). Particularly, the Spearman's rank correlation coefficient is a robust measure of similarity between rankings. When the coefficient score is one, the two rankings coincide and, consequently, ranking is not affected by the particular DEA model, while a score of 0 indicates that rankings are absolutely different. The Pearson and Spearman's rank correlation measurements always score less than one, varying from 0.168 to 0.993 and from 0.188 to 0.989, respectively. As expected, there is a high correlation between DEA cross-efficiencies and the comprehensive index both in terms of efficiency scores and ranks. Both the efficiency measurements and ranks of Model A and the Sole24Ore study are weakly correlated to the efficiency measurements and ranks obtained for the XECI model.

Table 5. Importance degrees of DEA cross-efficiency models.

Importance Degree	Model B	Model C	Model D	Model E	Model F	Model G
H_p	0.99477	0.99491	0.99486	0.99450	0.99483	0.99512
d_p	0.00523	0.00509	0.00514	0.00550	0.00517	0.00488
W_p	0.16869	0.16425	0.16586	0.17721	0.16662	0.15737

Table 6. Pearson Correlations between ecological efficiency indices.

	Model A	Model B	Model C	Model D	Model E	Model F	Model G	XECI	Sole24Ore
Model A	1.000	0.592	0.576	0.540	0.597	0.546	0.578	0.583	0.188
Model B	0.592	1.000	0.976	0.876	0.978	0.930	0.970	0.974	0.323
Model C	0.576	0.976	1.000	0.896	0.955	0.966	0.991	0.984	0.349
Model D	0.540	0.876	0.896	1.000	0.895	0.953	0.922	0.951	0.272
Model E	0.597	0.978	0.955	0.895	1.000	0.935	0.969	0.975	0.317
Model F	0.546	0.930	0.966	0.953	0.935	1.000	0.978	0.985	0.365
Model G	0.578	0.970	0.991	0.922	0.969	0.978	1.000	0.993	0.375
XECI	0.583	0.974	0.984	0.951	0.975	0.985	0.993	1.000	0.340
Sole24Ore	0.188	0.323	0.349	0.272	0.317	0.365	0.375	0.340	1.000

Table 7. Spearman Order Correlations between ranks.

	Model A	Model B	Model C	Model D	Model E	Model F	Model G	XECI	Sole24Ore
Model A	1.000	0.567	0.568	0.484	0.577	0.510	0.561	0.559	0.168
Model B	0.567	1.000	0.942	0.867	0.960	0.899	0.945	0.965	0.290
Model C	0.568	0.942	1.000	0.858	0.896	0.955	0.983	0.978	0.288
Model D	0.484	0.867	0.858	1.000	0.865	0.908	0.887	0.924	0.243
Model E	0.577	0.960	0.896	0.865	1.000	0.873	0.933	0.947	0.271
Model F	0.510	0.899	0.955	0.908	0.873	1.000	0.959	0.965	0.323
Model G	0.561	0.945	0.983	0.887	0.933	0.959	1.000	0.989	0.331
XECI	0.559	0.965	0.978	0.924	0.947	0.965	0.989	1.000	0.297
Sole24Ore	0.168	0.290	0.288	0.243	0.271	0.323	0.331	0.297	1.000

Finally, Table 8 reports measurements relative to the ecological efficiency comprehensive index XECI of cities grouped by geographical area and population class. Three population classes have been used for grouping cities—"less than 80,000" inhabitants, "between 80,000 and 200,000" inhabitants and "more than 200,000" inhabitants—as in the Sole24Ore ranking technical report. Except for the largest cities located in the isles ("more than 200,000" inhabitants cities), the mean comprehensive ecological efficiency generally increases when the size of the cities increases. Indeed, the mean efficiency is between 56.7% and 59.4% in smaller cities ("less than 80,000" inhabitants), and between 62.4% and 65.7% in medium size cities ("between 80,000 and 200,000" inhabitants). In the last group of cities ("more than 200,000" inhabitants), the mean ecological efficiency achieves higher scores in the North, Center and South of Italy, but sharply decreases in the last group of cities located in the isles, because of the lower efficiency values earned by the cities of Catania and Palermo.

Table 8. Measurements of the Shannon's entropy index (XECI) for cities grouped by geographical area and population size.

	Less Than 80,000			**between 80,000 and 200,000**			**More Than 200,000**		
	Cities	*XECI*	*Population*	*Cities*	*XECI*	*Population*	*Cities*	*XECI*	*Population*
North	Imperia	0.111	42,230	Treviso	0.288	80,822	Venezia	0.575	261,555
	Belluno	0.408	35,595	Alessandria	0.550	89,613	Trieste	0.645	202,346
	Pavia	0.552	68,449	Ferrara	0.587	132,588	Padova	0.694	206,284
	Mantova	0.560	46,593	Como	0.612	81,794	Verona	0.713	252,720
	Pordenone	0.566	50,499	Ravenna	0.618	153,096	Torino	0.717	871,816
	Lodi	0.579	43,285	Vicenza	0.629	111,755	Bologna	0.727	370,402
	Cremona	0.588	69,839	Udine	0.644	98,246	Genova	0.745	586,162
	Rovigo	0.590	50,040	Forlì	0.644	116,242	Milano	0.815	1,235,543
	Vercelli	0.598	46,179	Novara	0.650	101,922			
	Biella	0.603	43,855	Bergamo	0.652	115,294			
	Lecco	0.612	46,628	Parma	0.652	175,536			
	Asti	0.614	73,874	Reggio Emilia	0.662	162,093			
	Savona	0.617	60,764	Piacenza	0.664	100,109			
	Gorizia	0.618	35,186	Monza	0.685	119,950			
	Varese	0.627	79,654	La Spezia	0.692	92,604			
	Cuneo	0.632	54,857	Modena	0.701	178,962			
	Sondrio	0.634	21,684	Brescia	0.717	189,331			
	Verbania	0.711	30,327	Bolzano	0.724	102,214			
	Aosta	0.839	34,144	Rimini	0.732	139,360			
				Trento	0.798	113,900			
	mean	0.582	49,141	mean	0.645	122,771	mean	0.704	498,353
	max	0.839	79,654	max	0.798	189,331	max	0.815	1,235,543
	min	0.111	21,684	min	0.288	80,822	min	0.575	202,346
	stdev	0.139	15,558	stdev	0.101	33,195	stdev	0.071	377,272
Center	Macerata	0.472	42,013	Pistoia	0.470	89,154	Firenze	0.608	356,869
	Frosinone	0.479	46,803	Pisa	0.526	85,901	Roma	0.742	2,611,397
	Rieti	0.490	46,098	Arezzo	0.532	97,965			
	Fermo	0.557	36,899	Lucca	0.569	86,818			
	Ascoli Piceno	0.564	50,081	Terni	0.601	109,295			
	Viterbo	0.581	62,947	Pesaro	0.620	94,440			
	Massa	0.615	68,847	Latina	0.631	117,746			
	Grosseto	0.677	78,475	Ancona	0.660	100,696			
	Siena	0.721	52,843	Perugia	0.664	161,910			
				Livorno	0.788	156,891			
				Prato	0.802	185,153			
	mean	0.573	53,889	mean	0.624	116,906	mean	0.675	1,484,133
	max	0.721	78,475	max	0.802	185,153	max	0.742	2,611,397
	min	0.472	36,899	min	0.470	85,901	min	0.608	356,869
	stdev	0.087	13,539	stdev	0.103	34,790	stdev	0.094	1,594,192

Table 8. *Cont.*

	Less Than 80,000			between 80,000 and 200,000			More Than 200,000		
	Cities	*XECI*	*Population*	*Cities*	*XECI*	*Population*	*Cities*	*XECI*	*Population*
South	Benevento	0.212	61,573	Catanzaro	0.534	89,523	Taranto	0.569	200,255
	Crotone	0.532	58,913	Lecce	0.566	89,492	Napoli	0.693	961,884
	Chieti	0.561	51,513	Pescara	0.589	117,239	Bari	0.723	315,946
	Isernia	0.564	21,957	Reggio Calabria	0.594	180,949			
	Cosenza	0.570	69,502	Foggia	0.635	147,481			
	Campobasso	0.586	48,798	Andria	0.636	99,976			
	L'Aquila	0.610	67,196	Brindisi	0.661	88,698			
	Trani	0.622	55,745	Barletta	0.681	94,122			
	Teramo	0.641	54,200	Salerno	0.842	132,794			
	Potenza	0.646	66,771						
	Vibo Valentia	0.649	33,422						
	Caserta	0.698	75,578						
	Avellino	0.701	54,309						
	Matera	0.720	59,750						
	mean	0.594	55,659	mean	0.638	115,586	mean	0.662	492,695
	max	0.720	75,578	max	0.842	180,949	max	0.723	961,884
	min	0.212	21,957	min	0.534	88,698	min	0.569	200,255
	stdev	0.124	14,158	stdev	0.090	32,357	stdev	0.082	410,426
Isles	Enna	0.369	27,907	Siracusa	0.548	118,888	Catania	0.221	294,461
	Agrigento	0.403	58,216	Cagliari	0.700	149,937	Palermo	0.335	658,078
	Tempio Pausania	0.407	13,951	Sassari	0.724	123,677	Messina	0.624	243,380
	Nuoro	0.431	36,682						
	Caltanissetta	0.436	61,697						
	Iglesias	0.464	27,688						
	Trapani	0.561	69,177						
	Ragusa	0.594	69,832						
	Olbia	0.621	53,079						
	Lanusei	0.627	5,488						
	Villacidro	0.654	14,291						
	Sanluri	0.666	8,460						
	Carbonia	0.729	28,885						
	Oristano	0.762	31,166						
	Tortolì	0.782	10,716						
	mean	0.567	34,482	mean	0.657	130,834	mean	0.393	398,639
	max	0.782	69,832	max	0.724	149,937	max	0.624	658,078
	min	0.369	5,488	min	0.548	118,888	min	0.221	243,380
	stdev	0.140	22,601	stdev	0.095	16,716	stdev	0.208	226,127

5. Conclusions

The prosperity and the development of nations are largely influenced by the growth of their cities. While cities are an important source of growth and economic competitiveness, at the same time, they are huge consumers of resources and energy, and producers of waste and greenhouse gas emissions.

In the last two decades, a number of factors have induced the policy makers and city planners to rethink the development and management model of cities, such as the advent of climate change, the shortage of fossil fuels and natural resources, the high costs related to the solid waste disposal, the increasing traffic congestion and the unpropitious impact of pollution on human health. In this context, improving the city ecological efficiency has become an important task of local administrators to make their cities more attractive, livable and environmentally sustainable. Measuring the results of the policies and actions implemented to enhance the sustainability level of cities is thus necessary to assess their effectiveness and efficiency. Rankings and benchmarking studies can be indeed an important tool for the city administration to make the city more ecologically efficient and environmentally sustainable, attractive and, finally, more competitive. Placing at a high rank of the ranking helps improving the image of the city and the reputation of the local government, and, as a consequence, can have an important role to support the marketing strategy of the city and attract funds from the central government and the private sector.

However, ranking metrics and methodologies often suffer from methodological drawbacks and remain opaque with a high degree of subjectivity related to the choice of indicators and, particularly, weighting schemes. Indeed, using ranking methods based on subjective weighting schemes may be inappropriate as weights reflect the preferences of a specific audience. Rankings can be very sensitive to weights and even very small changes in the weighting scheme can seriously impact the ranking order, and it is common that they are many times open to manipulation.

This paper has proposed a robust and transparent method that implements Data Envelopment Analysis and the Shannon's entropy index to construct an aggregated measurement of city sustainability in the form of an ecological efficiency comprehensive index. The proposed methodological framework has the advantage to combine together a set of indicators that reflect the diversity of many ecological efficiency areas and different evaluation perspectives. In the method, the weighting scheme used to aggregate partial indicators is generated endogenously from the data. In addition, the flexibility of the method allows the inclusion of a variable set of indicators in order to customize the measurement of the ecological efficiency index to the specific needs of the context, and, more important, to the availability of data.

As an empirical application, the index has been used to measure the ecological efficiency for a sample of 116 Italian provincial capital cities. The outcome of city rankings highlights a remarkable variability in the sample of cities. The score of the comprehensive index that measures the ecological efficiency is between 11.05% and 84.21%. In particular, on the one hand, there are a large number of cities where, over years, the local governments planned and implemented several projects and specific policies to improve urban environmental sustainability. These cities achieved a higher ecological efficiency score and perform better on the ranking. This is the case of Salerno (84.2%) in the South of Italy, Aosta (83.9%), Genova (74.5%), Milano (81.5%) and Trento (79.8%) in the North, Livorno (78.8%), Prato (80.2%) and Roma (74.2%) in the Center, and Oristano (76.2%) and Tortolì (78.2%) in the Isles. On the other hand, there are urban contexts where there is still a lack of attention to environmental issues and sustainability, above all as a consequence of the territorial, economic and infrastructural divide. As a general behavior, the ecological efficiency measurement increases when the size of the city increases. However, the largest cities which are located in the Isles are poorly performing. Differences between cities can be even more marked than differences between regions.

Results show that the proposed DEA framework based on the implementation of various cross-efficiency DEA models and the Shannon's entropy index produces an evaluation of the city ecological efficiency that differs from that provided by the economic newspaper Sole24Ore which is typically assumed as a reference in Italy for city comparisons. Main reasons of this difference are the utilization of a different set of environment-related statistics and of subjective weights introduced in the calculation of the index provided by the Sole24Ore study. On the contrary, the adoption of DEA as a general method limits the subjectivity needed for the analysis to the choice of the DEA models (*i.e.*, the input and output variables). In this way, a ranking of cities with respect to their ecological efficiency can be generated by means of a more objective methodology. Therefore, using DEA as a method for generating an ecological efficiency measurement allows having some degree of standardization and comparability. Moreover, the DEA-Shannon's entropy based index provides useful and easy-to-communicate information to rank and compare cities with respect to their environmental sustainability with an acceptable discrimination capability.

The city governments can use the ranking measurements generated by the index to conduct useful benchmarking analyses, and identify the city strengths and weaknesses compared with peer cities. Furthermore, performing a more in-depth analysis within the group of city peers looking at the measurements of individual indicators used to construct the comprehensive measurement can suggest where the city has to improve to increase its progress to ecological efficiency by monitoring the performance of the city over time. Benchmarking and city rankings are fundamental pre-requisites for the political decision makers and administrators to give account of their actions, forcing them to make their decisions transparent and comprehensible to stakeholders, becoming an important tool to promote democracy and participation by attracting attention and stimulating discussion on sustainable strategies, and supporting shared learning. Thus, the proposed index becomes an indispensable tool for the development of plans and policy measures to promote the ecological efficiency in the cities.

Of course, measuring the city ecological efficiency is not an exact science. The development of the proposed index is a work in progress, and a longitudinal analysis is necessary to further test its strengths or weaknesses. It has been computed for one single year, providing a static representation of the ecological efficiency scores of the cities in the sample, but its calculation can be easily extended to several years if reliable and objective data are available to perform benchmarking analyses over time. There are some critical non-discretionary variables that are beyond the control of the city government which can influence the ecological efficiency measurement and, henceforth, need consideration. A more in depth research effort should take into account factors such as climate, territory topology, infrastructure development, and so on. Unlike country or regional data which are generally available thanks to the work carried on by the National Statistical Offices, collecting data at the city level is still at the beginning. Therefore, the lack of reliable, high quality and cost effective data is a major challenge, no matter how the ranking methodology can be rigorous and supported by a sound theory. Moreover, even though the relevant advantage of the method is its objectivity, the extreme flexibility of DEA allows the introduction in the model of thresholds, weight restrictions, and economic payoffs that take into account specific policy goals.

It should be recognized that city comparisons and the examination of the effect of policies and measures to support city sustainability are complex and require a more in depth analysis than that allowed by a single ranking index. Thus, caution is necessary when the proposed index is used to assess the efficacy of environmental policies. According to literature relative to the measurement of urban sustainability and ecological efficiency no single indicator set or index are appropriate for every application and implementable in practice. Henceforth, the proposed comprehensive index should not be considered as a substitute, but rather utilized together with other methods.

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Appendix

Supposing that the set of input variables is partitioned into the subset of discretionary input variables (I_D) and the subset of non-discretionary (uncontrollable) input variables (I_{ND}) so that $I_D \cup I_{ND} = I = \{1, \ldots, m\}$ and $I_D \cap I_{ND} = \varnothing$, models (3), (4), (5) and (6) are modified as follows:

$$\begin{gathered}
\text{Max} \sum_{r=1}^{s} u_{rk} y_{rk} - \sum_{i \in I_{ND}} v_{ik} x_{ik} + u_{*k} \\
\text{s.t.} \quad \sum_{i \in I_D} v_{ik} x_{ik} = 1 \\
\sum_{r=1}^{s} u_{rk} y_{rj} - \left(\sum_{i \in I_D} v_{ik} x_{ij} + \sum_{i \in I_{ND}} v_{ik} x_{ij} \right) + u_{*k} \leqslant 0 \quad j = 1, \ldots, n \\
u_{rk} \geqslant 0, v_{ik} \geqslant 0, \; u_{*k} \text{ free}, \quad i \in I_D, i \in I_{ND} \text{ and } r = 1, \ldots, s
\end{gathered} \tag{3'}$$

$$E_{kk} = \frac{\sum_{r=1}^{s} u_{rk}^{*} y_{rk} - \sum_{i \in I_{ND}} v_{ik}^{*} x_{ik} + u_{*k}}{\sum_{i \in I_D} v_{ik}^{*} x_{ik}} \quad i \in I_D, \; i \in I_{ND} \tag{4'}$$

$$E_{kj} = \frac{\sum_{r=1}^{s} u_{rk}^{*} y_{rj} - \sum_{i \in I_{ND}} v_{ik}^{*} x_{ij} + u_{*k}}{\sum_{i \in I_D} v_{ik}^{*} x_{ij}} \quad i \in I_D, i \in I_{ND}, j \neq k \quad \text{and} \quad j = 1, \ldots, n \tag{5'}$$

$$\begin{aligned} \min \quad & \sum_{r=1}^{s} u_{rk} \left(\sum_{j=1, j\neq k}^{n} y_{rj} \right) - \sum_{i \in I_{ND}} v_{ik} \left(\sum_{j=1, j\neq k}^{n} x_{ij} \right) + u_{*k} \\ \text{s.t.} \quad & \sum_{i \in I_D} v_{ik} \left(\sum_{j=1, j\neq k}^{n} x_{ij} \right) = 1 \\ & \sum_{r=1}^{s} u_{rk} y_{rk} - \sum_{i \in I_{ND}} v_{ik} x_{ik} - E_{kk}^{*} \sum_{i \in I_D} v_{ik} x_{ik} + u_{*k} = 0 \\ & \sum_{r=1}^{s} u_{rk} y_{rj} - \sum_{i \in I_D} v_{ik} x_{ij} - \sum_{i \in I_{ND}} v_{ik} x_{ij} + u_{*k} \leqslant 0 \\ & u_{rk} \geqslant 0, v_{ij} \geqslant 0, u_{*k} \text{ free}, \quad i \in I_D, i \in I_{ND}, \quad j = 1, \ldots, n \quad \text{for} \quad j \neq k, \quad r = 1, \ldots, s. \end{aligned} \tag{6'}$$

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